Automated anomalous child repetitive head movement identification

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***Abstract*—This paper will focus and elaborate upon identification of repetitive child head movement and its Finite automata representation. The paper is split into the following, Introduction where the problem is introduced, Applications the benefits of identifying head movement at an early stage,Literature review where further elaboration of the NFA and its integrations is shown, Addressed using Finite automata where our model will be explained in further details, experimental setup where will show the code behind our NFA simulation, Simulation results where we'll test out our model with a few inputs, and finally Future considerations where we'll conclude our paper. The goal of this paper is to clarify and show how the final model was reached by explaining every step that has lead to it.**

***Index Terms*—children, head movement, Deterministic Finite Automata (DFA),Nondeterministic Finite Automata (NFA)**

I. Introduction

The problem faced in this paper is how vital it is to identify early signs of mental disorders in children using their head movement, it aid parents to treat their kids as early as possible to have a higher chance of psychological treatment or in some cases where it cannot be treated at least the parents would be aware of how to treat and act around their child to be more understanding of their condition.

II. Applications

A. Importance of Early Identification

The importance of early identification and intervention plays an important role in detecting and helping children with behavioral disorders. By developing an automated model, the detection of typing and atypical repetitive head movements can be analyzed through videos. This research aims to help the healthcare industry by providing it with an automated model that can speed up the process and early detect any issues. This research provides an insight into removing diagnostic issues, speeding up certain processes through automation, and classification performances from other research.[1]

B. Diagnostic Challenges and Automation for Diagnosis

Traditional diagnostic methods for behavioral disorders encounter several challenges in the process of creating them. Challenges such as limited facilities and shortage of healthcare specialists. This research provides a solution by presenting an automated approach that utilizes advanced technologies and machine learning algorithms to analyze videos. This automation helps speed up the process by removing any limitations that we traditionally face. This can be highly beneficial in regions that don't have the right healthcare services and medical professionals. An automated robot would result in an efficient and resource saving solution.[1]

C. Classification Performance and Dataset Development

This research utilizes the study of transformer networks and Non-Deterministic Finite Automata (NFA) techniques to classify these repetitive head movements in children. Through several experiments with various transfer learning methods, the automated model outperformed several frameworks. These advancements would contribute significantly to more accurate and reliable diagnoses of behavioral disorders. This study also raises the issue with the limited publicly available organized child datasets. This limitation was recognized by the research, and this is beneficial to any future research conducted on this matter.[1]

Fig. 1: An example of gesture detection software.[2]

III. Literature review

This paper focuses on multiple ways of identifying repetitive head movements in children to try and identify certain behavioral disorders, like autism, X syndrome, and Prader-Willi syndrome. They used a combination of a Nondeterministic finite automata (NFA) as well as transformer networks (which is a deep learning algorithm) which identify if the head movement is typical or atypical. The model worked as followed, First the video data of children head movement would be given to the Head movement classifer (HMC) which is the transformer network, after the type of head movement is classified by the model, it will then give the output to the Periodic analysis model(PAM) which is the NFA to identify the count and frequency of the head movement, after which the combined outputs of both the HMC and the PAM will go to another network classifier called SAM which then identifies the behavioral patterns.[1]

A. Periodic analysis model(PAM)

The PAM NFA is as follows, it has 3 states starting(Ss), Away(Sa), and towards(St). Starting signals that repetitive head movement has began, Away is when the individual moves their head away from the starting position, and towards is when the individual moves their head towards the starting position. these states are transitions to by the translation of the 3D movement of the nose in the video. there are 3 alphabet letters: 'a' which is when the current 3D position is 0 or a constant value, 'b' is when the value of the 3D position is greater than the previous 3D value, and 'c' is when the 3D value is less than that of the previous value.[1]

IV. Addressed using Finite Automata

Using the PAM model we are trying to recreate from the paper, to identify the count and frequency at which the head movement occurs, but the paper is able to keep track of that due to the multitude of other parameters and systems it is using in conjunction with the NFA. The NFA is it stands detects 2 main things whether the head movement is periodic or aperiodic. If the NFA accepts that means the head movement is periodic if it fails that means it is aperiodic. The NFA is formally defined as the following:

$PAM = (S, \sum, \delta, q_0, F)$

where,

$S = \{Ss, Sa, St\}$,

$\sum = \{a, b, c\}$,

$q_0 = Ss$,

$F = Ss$,

$\delta =$

	a	b	c
Ss	Ss	Sa	ϕ
Sa	ϕ	Sa	St
St	Ss	Sa	St

V. Experimental setup

A. NFA setup

We used Python with the Automata library to simulate the previously defined NFA due to some issues that were ran into in the code we found it was best suited to transform the NFA to a DFA sense it will neither change its meanings nor its results. the DFA was defined in the code as in the following figure, As you can see We only very slightly altered the original NFA by simple adding a reject state for all the unused transitions.

```
from automata.fa.dfa import DFA

dfa = DFA(
    states={'Ss', 'Sa', 'St', 'reject'},
    input_symbols={'a', 'b', 'c'},
    transitions={
        'Ss': {'a': 'Ss', 'b': 'Sa', 'c' : 'reject'},
        'Sa': {'a': 'reject', 'b': 'Sa', 'c': 'St'},
        'St': {'a': 'Ss', 'b': 'Sa', 'c': 'St'},
        'reject': {'a' : 'reject', 'b': 'reject', 'c': 'reject' }
    },
    initial_state='Ss',
    final_states={'Ss'}
)
```

Fig. 2: DFA Code

The library is relatively simple in the way it is used. By simply giving the formal definition format to the DFA class it constructs the DFA as you intend.

After a bit of Editorial work from the team we have found a way to improve upon our DFA by turning to its original NFA state and adding a counting function to simulate the counting of repetitive head movements. As well as an improved outputting function for better understand-ability and usability.

```
from automata.fa.nfa import NFA

pam_nfa = NFA(
    states={'Ss', 'Sa', 'St'},
    input_symbols={'a', 'b', 'c'},
    transitions={
        'Ss': {'a': {'Ss'}, 'b': {'Sa'}},
        'Sa': {'b': {'Sa'}, 'c': {'St'}},
        'St': {'a': {'Ss'}, 'b': {'Sa'}, 'c': {'St'}},
    },
    initial_state='Ss',
    final_states={'Ss'}
)
```

Fig. 3: NFA Code

```
def countrepeats(instring):
    count = instring.count("bca")
    return count


def test_nfa(instring):
    current_states = {pam_nfa.initial_state}
    print('\nSteps:')
    s = ""
    for symbol in instring:
        s += f"Current states: {current_states}, Input: {symbol} -> "
        next_states = set()
        for state in current_states:
            next_states |= pam_nfa.transitions[state].get(symbol, set())
        current_states = next_states
        s += f"Next states: {current_states}\n"

        if not current_states:
            s += 'Rejected'
            print(s)
            return

    if current_states & pam_nfa.final_states:
        s += 'Accepted'
    else:
        s += 'Rejected'
    print(s)
    if "Accepted" in s:
        print("Number of repeated head movements:", countrepeats(instring))

test_nfa("abcaaabcabbca")
```

Fig. 4: Counting function and Testing Code

B. *Abstract neural network model*

To further approach what the paper has offered we tried with our limited knowledge of deep learning to create some type of head detection model that could be improved at a later time to detect repetitive head movement and classify it. The model works as followed. After manually labeling 180 images that were taken of myself, I then started processing the images and putting them in a way the model could understand then I used a library called Albumentations that created multiple variants of each picture by altering the horizontal and vertical flips as well as adjusting gamma among a whole other set of alterations that basically increased our data size by 60 times. After all the data splitting and preparation was done the neural network model was then set up with a 2 layer system one to predict if the head is on screen or not using the sigmoid function and the other is a regression layer to predict where the head is positioned on screen. here are some examples:

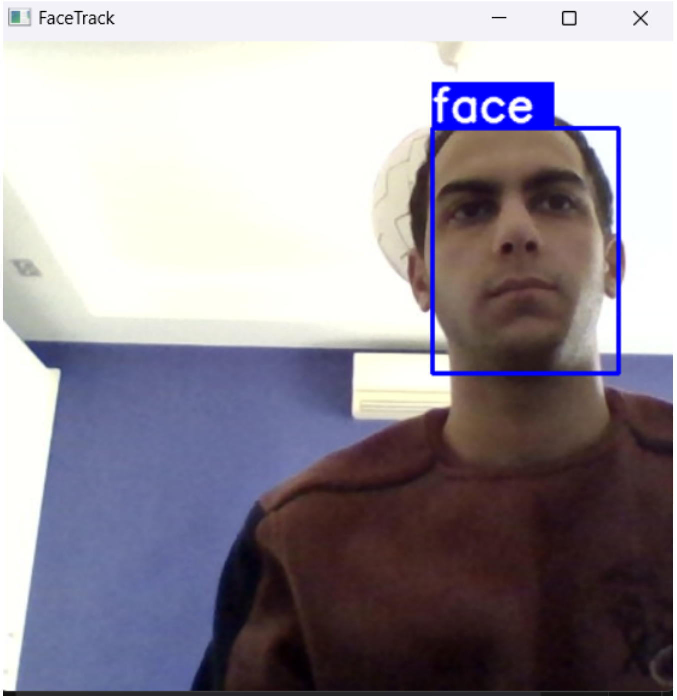

Fig. 5: Face track 1

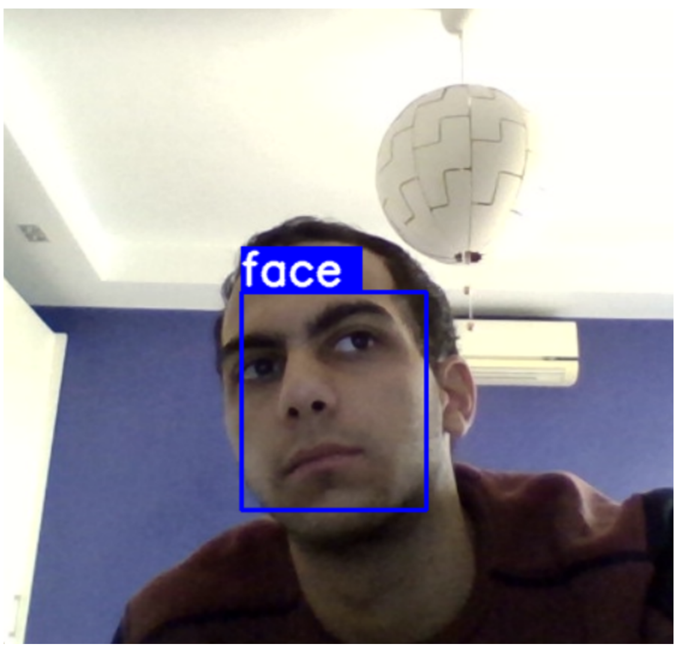

Fig. 6: Face track 2

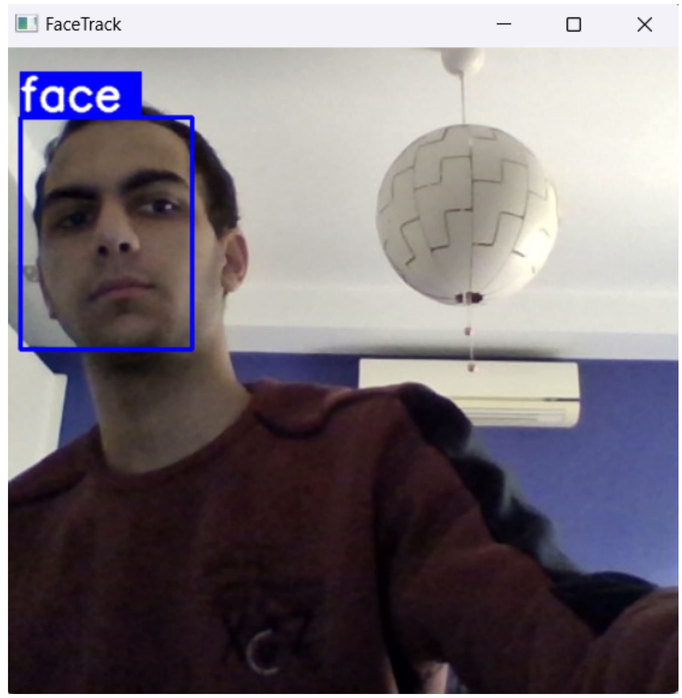

Fig. 7: Face track 3

through my experimentation with this model I now understood why the use of the nose 3D space is way more accurate than the face as my head could tilt left and right and the box will still barely move signifying loss in accuracy if this model was used for head movement classification.

VI. Simulation results

Using the testing function we have created to simulate the HMC model pretranslated inputs of nose's x,y,z positions.which get inputted as an NFA alphabet of a,b,and c to be run on the PAM model and count the number of repetitions of the head movement. As said previously the model only accept periodic head movement and reject aperiodic head movements.

A. accepted inputs

test 1 input(abcabca):

Current states: 'Ss', Input: a -> Next states: 'Ss'
Current states: 'Ss', Input: b -> Next states: 'Sa'
Current states: 'Sa', Input: c -> Next states: 'St'
Current states: 'St', Input: a -> Next states: 'Ss'
Current states: 'Ss', Input: b -> Next states: 'Sa'
Current states: 'Sa', Input: c -> Next states: 'St'
Current states: 'St', Input: a -> Next states: 'Ss'

Accepted
Number of repeated head movements: 2

test 2 input(abcaaabcabbca):
Current states: 'Ss', Input: a -> Next states: 'Ss'
Current states: 'Ss', Input: b -> Next states: 'Sa'
Current states: 'Sa', Input: c -> Next states: 'St'
Current states: 'St', Input: a -> Next states: 'Ss'
Current states: 'Ss', Input: a -> Next states: 'Ss'
Current states: 'Ss', Input: a -> Next states: 'Ss'
Current states: 'Ss', Input: b -> Next states: 'Sa'
Current states: 'Sa', Input: c -> Next states: 'St'
Current states: 'St', Input: a -> Next states: 'Ss'
Current states: 'Ss', Input: b -> Next states: 'Sa'
Current states: 'Sa', Input: b -> Next states: 'Sa'
Current states: 'Sa', Input: c -> Next states: 'St'
Current states: 'St', Input: a -> Next states: 'Ss'
Accepted
Number of repeated head movements: 3

test 3 input(bca):
Current states: 'Ss', Input: b -> Next states: 'Sa'
Current states: 'Sa', Input: c -> Next states: 'St'
Current states: 'St', Input: a -> Next states: 'Ss'
Accepted
Number of repeated head movements: 1

B. rejected inputs

test 1 input(bcb):
Current states: 'Ss', Input: b -> Next states: 'Sa'
Current states: 'Sa', Input: c -> Next states: 'St'
Current states: 'St', Input: b -> Next states: 'Sa'
Rejected

test 2 input(abbcbccc):
Current states: 'Ss', Input: a -> Next states: 'Ss'
Current states: 'Ss', Input: b -> Next states: 'Sa'
Current states: 'Sa', Input: b -> Next states: 'Sa'
Current states: 'Sa', Input: c -> Next states: 'St'
Current states: 'St', Input: b -> Next states: 'Sa'
Current states: 'Sa', Input: c -> Next states: 'St'
Current states: 'St', Input: c -> Next states: 'St'
Current states: 'St', Input: c -> Next states: 'St'
Rejected

test 3 input(abbbbbb):
Current states: 'Ss', Input: a -> Next states: 'Ss'
Current states: 'Ss', Input: b -> Next states: 'Sa'
Current states: 'Sa', Input: b -> Next states: 'Sa'
Current states: 'Sa', Input: b -> Next states: 'Sa'
Current states: 'Sa', Input: b -> Next states: 'Sa'
Current states: 'Sa', Input: b -> Next states: 'Sa'
Current states: 'Sa', Input: b -> Next states: 'Sa'
Rejected

VII. Future considerations

The issues that arise when trying to implement this model into the medical field can be split into three categories, data issues, the limit of the model, and other real-world factors. Data concerns are a massive problem when comes to the field of artificial intelligence, since almost all work is dependent on the data used to train these models to have an impact in real-world situations. Model limitations also present an issue due to the fact that the model can be explicit and hard to generalize across the populous, how explainable the model can be is also an important factor, as well as the possibility of false positives/negatives being present in most cases.

The data that is available to be able to this kind of research is not enough to get a medically accurate and semi-perfect accuracy model to work. RRHM datasets are scarce as is, and adding children to the equation makes it harder to find. If however, a dataset that can be used properly is found, it will often be imbalanced between typical and atypical, which could lead to overfitting, making it a non-viable option for real-world applications. Labeling of data poses a problem as well, since the term "anomaly" can subjective and can differ from one person to another, also "anomalies" can be subtle and hard to identify from normal behaviors, which could lead to inconsistencies when labeling the data, making the model less accurate and less feasible for real-world deployment. Another minor issue that arises is privacy concerns and potentially ethical concerns on recording and analyzing video data of children.

The next problem is the limitations of the models that can be implemented. If the model is trained on one specific data set, then it cannot be used to generalize the identification of abnormal head movements, since it could produce multiple false positives/negatives, which would make the model extremely unreliable and non-viable in real-world situations. Also, the explainability of understanding how RRHM's work is crucial for the trust and responsible application of this model, especially in the healthcare sector, which should be as accurate as possible.

Aside from data and model limitations, there are other real-world factors that play a role in implementing this kind of system in healthcare. Mainly cost and accessibility would be a massive issue, since deploying and maintaining this kind of system can be expensive, meaning that it would be reserved for the higher-class community, leaving many people unable to be diagnosed. Integrating these kinds of systems in the healthcare system could also prove challenging since automated tools such as this system should seamlessly integrate into existing systems without the need for a long adaptation period.

There are few future directions that can be considered, but they could be crucial for making this a viable and productive system that can be implemented into current healthcare systems. We should try to collect larger and more diverse data to have proper/multiple datasets to work with so that the data isn't skewed/biased. Applying data augmentation techniques can also be of benefit when trying to increase accuracy of the training data, and defining a formal definition for what an anomaly is in this case as well as using other techniques that are like unsupervised learning can prove useful when trying to label the unlabeled data. For the limitation problems, the most we can do is develop more explainable and understandable transformers to perform the RRHM's work. The system would also have to be very user-friendly to seamlessly transition in the healthcare environment, as well as performing constant checks to see if the data was accurate in said real-world settings. As for the more general cost and ethical concerns, the methods used to obtain the data have to be inline with rules and regulations and basic morals, as well as trying to reduce the cost of the system as much as possible without sacrificing performance.

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